

Национальный исследовательский университет "МЭИ"



Кафедра РЗиА

Лабораторная работа № 4

«ГЛУБОКОЕ ОБУЧЕНИЕ ДЛЯ ПРОГНОЗИРОВАНИЯ
ВРЕМЕННОГО РЯДА»

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Проверил	Нухулов С.М.

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**ФЕДЕРАЛЬНОЕ ГОСУДАРСТВЕННОЕ БЮДЖЕТНОЕ
ОБРАЗОВАТЕЛЬНОЕ УЧРЕЖДЕНИЕ ВЫСШЕГО
ОБРАЗОВАНИЯ НАЦИОНАЛЬНЫЙ
ИССЛЕДОВАТЕЛЬСКИЙ УНИВЕРСИТЕТ
«МОСКОВСКИЙ ЭНЕРГЕТИЧЕСКИЙ ИНСТИТУТ»
Кафедра «РЗиАЭ»**

Лабораторная работа №4

Глубокое обучение для прогнозирования временного ряда.

Выполнил: студент группы Э-13м-19

Энтентеев А.Р.

Проверил: Нухулов С.М.

Москва, 2020

In [1]:

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Flatten, Dense, Activation, Dropout, BatchNormalization, Conv1D, GlobalMaxPooling1D, MaxPooling1D, GRU
from sklearn.preprocessing import MinMaxScaler
from tensorflow import keras
```

Подготовка данных

In [2]:

```
data = pd.read_csv("AEP_hourly.csv")
```

In [3]:

```
data = data.drop('Datetime',axis=1)
data.head()
```

Out[3]:

	AEP_MW
0	13478.0
1	12865.0
2	12577.0
3	12517.0
4	12670.0

Генератор для формирования обучающих пакетов

In [12]:

```
def generator(data, lookback, delay, min_index, max_index,
              shuffle = True, batch_size = 24, step = 2):
    if max_index is None:
        max_index = len(data)-delay-1
    i = min_index + lookback
    while 1:
        if shuffle:
            i = np.random.randint(min_index + lookback, max_index)
        if i + batch_size >= max_index:
            if shuffle:
                i = np.random.randint(min_index + lookback, max_index)
            else:
                i = min_index + lookback

        rows = np.arange(i, min(i + batch_size, max_index))
        i += len(rows)
        samples = np.zeros((len(rows), lookback // step,
                           data.shape[-1]))
        targets = np.zeros((len(rows),))
        for j, row in enumerate(rows):
            indices = range(rows[j] - lookback, rows[j], step)
            samples[j] = data.iloc[indices]
            targets[j] = data.iloc[rows[j] + delay] #[1]
        yield samples, targets
```

In [13]:

```
TrainGen = generator(data,48,1,0,63667,shuffle=True)
ValGen = generator(data,48,1,63668,84890,shuffle=True)
TestGen = generator(data,48,1,84891,121272,shuffle=True)
```

Наивный алгоритм

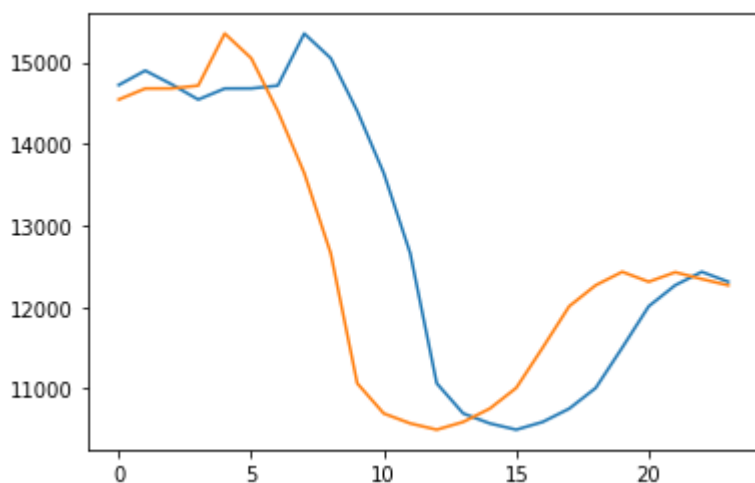
In [15]:

```
samples, targets = next(ValGen)
print(samples.shape)
prediction = samples[:, -1, 0]
plt.plot(prediction)
plt.plot(range(0, 24, 1), targets[0:24])
ME = np.mean(np.abs(prediction[0:24] - targets[0:24]))
MAE = np.mean(np.abs(prediction[0:24] - targets[0:24])/prediction[0:24])
print("Среднее отклонение = ", ME)
print("Среднее абсолютное отклонение = ", MAE)
```

(24, 24, 1)

Среднее отклонение = 864.875

Среднее абсолютное отклонение = 0.0662638835093408



Многослойный перцептрон

In [6]:

```
data = pd.read_csv("AEP_hourly.csv")
```

In [7]:

```
scaler = MinMaxScaler(feature_range=(0,1))
data = data.drop('Datetime',axis=1)
scaler.fit(data)
data = scaler.transform(data)
```

In [8]:

```
data = pd.DataFrame(data)
data
```

Out[8]:

	0
0	0.241839
1	0.203798
2	0.185925
3	0.182202
4	0.191697
...	...
121268	0.714162
121269	0.708576
121270	0.697468
121271	0.672335
121272	0.646146

121273 rows × 1 columns

In [32]:

```
TrainGen = generator(data,48,1,0,63667,shuffle=True)
ValGen = generator(data,48,1,63668,84890,shuffle=True)
TestGen = generator(data,48,1,84891,121216,shuffle=True)
```

In [51]:

```
def createModel():
#     NB_CLASSES = y_train.shape[1]
    INPUT_SHAPE = (24,1)
    model = Sequential()
    model.add(Flatten(input_shape=INPUT_SHAPE))
    model.add(Activation('relu'))
    model.add(Dense(32))
    model.add(Activation('relu'))
    model.add(Dense(32))
    model.add(Activation('relu'))
    model.add(Dense(8))
    model.add(Activation('relu'))
    model.add(Dropout(0.3))
    model.add(Dense(1))
    model.add(Activation('sigmoid'))
    model.summary()
    return model
```

In [52]:

```
def modelLearning(train_gen, val_gen, model, EPOCHS = 20):  
    hist = model.fit(train_gen, steps_per_epoch = 300, epochs = EPOCHS,  
                      verbose = 1, validation_data = val_gen, validation_steps = 2  
00)  
    return hist
```

In [53]:

```
def plotHistory(history):  
    epochs = history.epoch  
    plt.figure()  
    plt.plot(epochs, history.history["mae"])  
    plt.plot(epochs, history.history["val_mae"])  
    plt.legend(["mae", "val_mae"])  
    plt.show()
```

In [128]:

```
def plotGraph(model):  
    samples, targets = next(TestGen)  
    prediction = model.predict(samples)  
    plt.plot(targets)  
    plt.plot(prediction)
```

In [54]:

```
model_1 = createModel()
```

Model: "sequential_9"

Layer (type)	Output Shape	Param #
flatten_7 (Flatten)	(None, 24)	0
activation_15 (Activation)	(None, 24)	0
dense_24 (Dense)	(None, 32)	800
activation_16 (Activation)	(None, 32)	0
dense_25 (Dense)	(None, 32)	1056
activation_17 (Activation)	(None, 32)	0
dense_26 (Dense)	(None, 8)	264
activation_18 (Activation)	(None, 8)	0
dropout_11 (Dropout)	(None, 8)	0
dense_27 (Dense)	(None, 1)	9
activation_19 (Activation)	(None, 1)	0
Total params: 2,129		
Trainable params: 2,129		
Non-trainable params: 0		

In [55]:

```
model_1.compile(loss='mse',  
                optimizer = 'rmsprop',  
                metrics=["mae"])
```

In [56]:

```
history_1 = modelLearning(TrainGen,ValGen,model_1,20)
```


Epoch 1/20
300/300 [=====] - 5s 17ms/step - loss: 0.0255
- mae: 0.1294 - val_loss: 0.0203 - val_mae: 0.1187

Epoch 2/20
300/300 [=====] - 5s 17ms/step - loss: 0.0178
- mae: 0.1071 - val_loss: 0.0174 - val_mae: 0.1110

Epoch 3/20
300/300 [=====] - 4s 14ms/step - loss: 0.0129
- mae: 0.0890 - val_loss: 0.0120 - val_mae: 0.0887

Epoch 4/20
300/300 [=====] - 4s 14ms/step - loss: 0.0119
- mae: 0.0859 - val_loss: 0.0073 - val_mae: 0.0659

Epoch 5/20
300/300 [=====] - 4s 13ms/step - loss: 0.0110
- mae: 0.0825 - val_loss: 0.0125 - val_mae: 0.0909

Epoch 6/20
300/300 [=====] - 4s 13ms/step - loss: 0.0107
- mae: 0.0810 - val_loss: 0.0069 - val_mae: 0.0643

Epoch 7/20
300/300 [=====] - 4s 13ms/step - loss: 0.0104
- mae: 0.0794 - val_loss: 0.0066 - val_mae: 0.0628

Epoch 8/20
300/300 [=====] - 4s 13ms/step - loss: 0.0102
- mae: 0.0784 - val_loss: 0.0065 - val_mae: 0.0623

Epoch 9/20
300/300 [=====] - 4s 14ms/step - loss: 0.0100
- mae: 0.0774 - val_loss: 0.0076 - val_mae: 0.0672

Epoch 10/20
300/300 [=====] - 4s 13ms/step - loss: 0.0101
- mae: 0.0774 - val_loss: 0.0073 - val_mae: 0.0671

Epoch 11/20
300/300 [=====] - 4s 14ms/step - loss: 0.0090
- mae: 0.0722 - val_loss: 0.0072 - val_mae: 0.0645

Epoch 12/20
300/300 [=====] - 4s 13ms/step - loss: 0.0095
- mae: 0.0750 - val_loss: 0.0076 - val_mae: 0.0682

Epoch 13/20
300/300 [=====] - 4s 14ms/step - loss: 0.0088
- mae: 0.0724 - val_loss: 0.0064 - val_mae: 0.0618

Epoch 14/20
300/300 [=====] - 4s 13ms/step - loss: 0.0095
- mae: 0.0750 - val_loss: 0.0057 - val_mae: 0.0561

Epoch 15/20
300/300 [=====] - 4s 13ms/step - loss: 0.0090
- mae: 0.0736 - val_loss: 0.0069 - val_mae: 0.0646

Epoch 16/20
300/300 [=====] - 4s 14ms/step - loss: 0.0096
- mae: 0.0747 - val_loss: 0.0066 - val_mae: 0.0604

Epoch 17/20
300/300 [=====] - 4s 14ms/step - loss: 0.0084
- mae: 0.0701 - val_loss: 0.0076 - val_mae: 0.0664

Epoch 18/20
300/300 [=====] - 4s 14ms/step - loss: 0.0086
- mae: 0.0703 - val_loss: 0.0079 - val_mae: 0.0673

Epoch 19/20
300/300 [=====] - 4s 14ms/step - loss: 0.0092
- mae: 0.0734 - val_loss: 0.0066 - val_mae: 0.0624

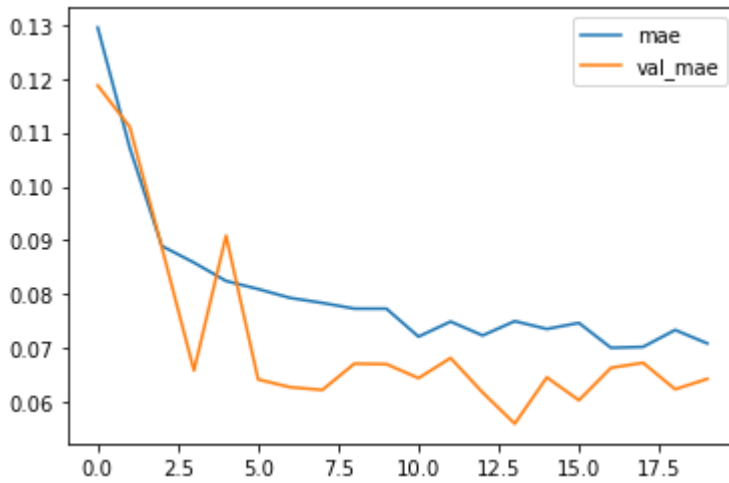
Epoch 20/20

300/300 [=====] - 4s 14ms/step - loss: 0.0087

- mae: 0.0709 - val_loss: 0.0068 - val_mae: 0.0644

In [57]:

```
plotHistory(history_1)
```



In [127]:

```
model_1.evaluate(TestGen, steps = 150)
```

150/150 [=====] - 1s 8ms/step - loss: 0.0075 -

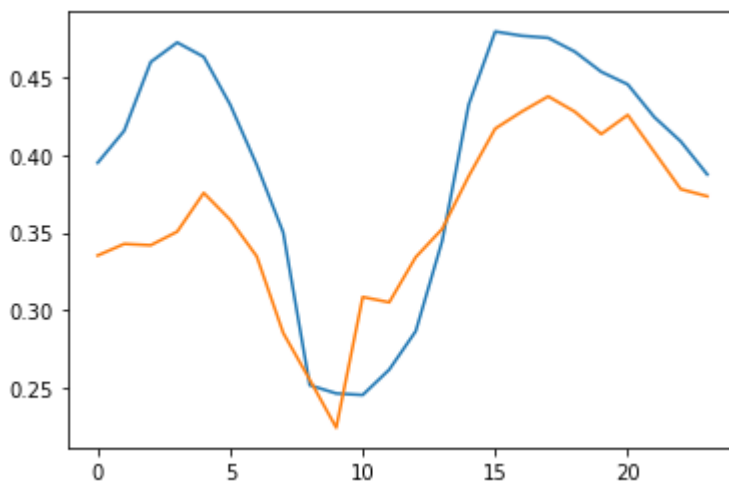
mae: 0.0646

Out[127]:

```
[0.0074824863113462925, 0.0646476000547409]
```

In [130]:

```
plotGraph(model_1)
```



Вывод:

Полученная модель получилась лучше, чем наивный подход и достигает среднего абсолютного отклонения 0,064 на тестовой выборке

Сверточная сеть

In [78]:

```
def createCONVmodel():
    INPUT_SHAPE = (24,1)
    model = Sequential()
    model.add(Conv1D(filters=32, kernel_size=6, activation='relu', input_shape=INPUT_SHAPE))
    model.add(MaxPooling1D(pool_size=2))
    model.add(Conv1D(filters=64, kernel_size=4, activation='relu'))
    model.add(MaxPooling1D(pool_size=2,padding = 'valid'))
    # model.add(Conv1D(filters=128, kernel_size=4, activation='relu'))
    # model.add(GlobalMaxPooling1D())
    model.add(Flatten())
    model.add(Dense(32, activation='relu'))
    model.add(Dropout(0.3))
    model.add(Dense(16, activation='relu'))
    model.add(Dropout(0.3))
    model.add(Dense(1,activation = 'sigmoid'))
    model.summary()
    return model
```

In [79]:

```
model_2 = createCONVmodel()
```

Model: "sequential_17"

Layer (type)	Output Shape	Param #
conv1d_30 (Conv1D)	(None, 19, 32)	224
max_pooling1d_26 (MaxPooling)	(None, 9, 32)	0
conv1d_31 (Conv1D)	(None, 6, 64)	8256
max_pooling1d_27 (MaxPooling)	(None, 3, 64)	0
flatten_11 (Flatten)	(None, 192)	0
dense_37 (Dense)	(None, 32)	6176
dropout_18 (Dropout)	(None, 32)	0
dense_38 (Dense)	(None, 16)	528
dropout_19 (Dropout)	(None, 16)	0
dense_39 (Dense)	(None, 1)	17
Total params: 15,201		
Trainable params: 15,201		
Non-trainable params: 0		

In [80]:

```
model_2.compile(loss='mse',  
                optimizer = 'rmsprop',  
                metrics=["mae"])
```

In [81]:

```
history_2 = modelLearning(TrainGen,ValGen,model_2,20)
```

Epoch 1/20
300/300 [=====] - 4s 14ms/step - loss: 0.0262
- mae: 0.1309 - val_loss: 0.0131 - val_mae: 0.0914

Epoch 2/20
300/300 [=====] - 4s 13ms/step - loss: 0.0149
- mae: 0.0965 - val_loss: 0.0154 - val_mae: 0.1032

Epoch 3/20
300/300 [=====] - 4s 14ms/step - loss: 0.0139
- mae: 0.0933 - val_loss: 0.0087 - val_mae: 0.0728

Epoch 4/20
300/300 [=====] - 4s 14ms/step - loss: 0.0122
- mae: 0.0863 - val_loss: 0.0083 - val_mae: 0.0703

Epoch 5/20
300/300 [=====] - 4s 14ms/step - loss: 0.0108
- mae: 0.0805 - val_loss: 0.0062 - val_mae: 0.0611

Epoch 6/20
300/300 [=====] - 4s 14ms/step - loss: 0.0100
- mae: 0.0775 - val_loss: 0.0074 - val_mae: 0.0675

Epoch 7/20
300/300 [=====] - 4s 14ms/step - loss: 0.0100
- mae: 0.0790 - val_loss: 0.0088 - val_mae: 0.0729

Epoch 8/20
300/300 [=====] - 4s 14ms/step - loss: 0.0095
- mae: 0.0754 - val_loss: 0.0083 - val_mae: 0.0705

Epoch 9/20
300/300 [=====] - 4s 14ms/step - loss: 0.0091
- mae: 0.0726 - val_loss: 0.0087 - val_mae: 0.0717

Epoch 10/20
300/300 [=====] - 4s 14ms/step - loss: 0.0094
- mae: 0.0755 - val_loss: 0.0071 - val_mae: 0.0637

Epoch 11/20
300/300 [=====] - 5s 16ms/step - loss: 0.0078
- mae: 0.0686 - val_loss: 0.0058 - val_mae: 0.0579

Epoch 12/20
300/300 [=====] - 5s 17ms/step - loss: 0.0081
- mae: 0.0688 - val_loss: 0.0068 - val_mae: 0.0649

Epoch 13/20
300/300 [=====] - 4s 15ms/step - loss: 0.0077
- mae: 0.0685 - val_loss: 0.0050 - val_mae: 0.0545

Epoch 14/20
300/300 [=====] - 4s 14ms/step - loss: 0.0084
- mae: 0.0701 - val_loss: 0.0061 - val_mae: 0.0588

Epoch 15/20
300/300 [=====] - 4s 15ms/step - loss: 0.0081
- mae: 0.0706 - val_loss: 0.0060 - val_mae: 0.0610

Epoch 16/20
300/300 [=====] - 5s 16ms/step - loss: 0.0071
- mae: 0.0651 - val_loss: 0.0055 - val_mae: 0.0577

Epoch 17/20
300/300 [=====] - 4s 14ms/step - loss: 0.0074
- mae: 0.0669 - val_loss: 0.0045 - val_mae: 0.0516

Epoch 18/20
300/300 [=====] - 4s 14ms/step - loss: 0.0075
- mae: 0.0668 - val_loss: 0.0069 - val_mae: 0.0638

Epoch 19/20
300/300 [=====] - 4s 15ms/step - loss: 0.0077
- mae: 0.0667 - val_loss: 0.0049 - val_mae: 0.0529

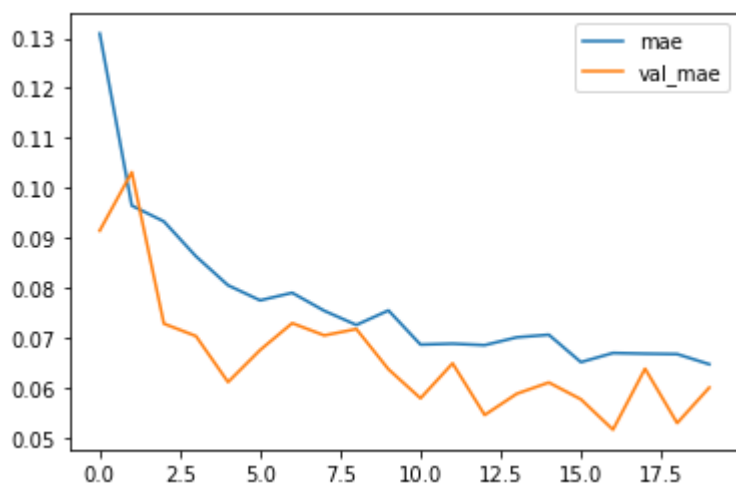
Epoch 20/20

300/300 [=====] - 4s 14ms/step - loss: 0.0070

- mae: 0.0647 - val_loss: 0.0061 - val_mae: 0.0600

In [83]:

```
plotHistory(history_2)
```



In [84]:

```
model_2.evaluate(TestGen, steps = 500)
```

1513/1513 [=====] - 16s 10ms/step - loss: 0.00

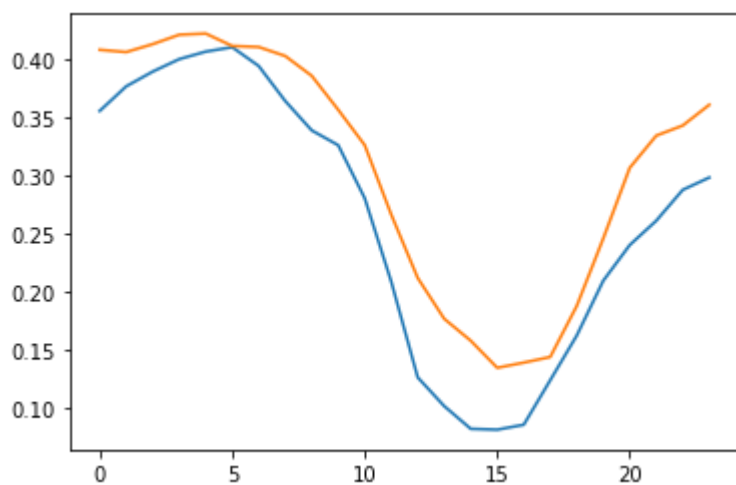
72 - mae: 0.0671

Out[84]:

```
[0.00719783129170537, 0.0670531839132309]
```

In [139]:

```
plotGraph(model_2)
```



Вывод:

Полученная модель получилась чуть хуже, чем многослойный перцептрон и достигает среднего абсолютного отклонения 0,67 на тестовой выборке

Рекуррентная сеть

In [93]:

```
def createRNNmodel():
    model = Sequential()
    model.add(GRU(32, input_shape = (None, 1)))
    model.add(Dense(1, activation = "sigmoid"))
    model.summary()
    return model
```

In [94]:

```
model_3 = createRNNmodel()
```

Model: "sequential_19"

Layer (type)	Output Shape	Param #
gru_1 (GRU)	(None, 32)	3360
dense_41 (Dense)	(None, 1)	33

Total params: 3,393
Trainable params: 3,393
Non-trainable params: 0

In [95]:

```
model_3.compile(loss='mse',
                 optimizer = 'rmsprop',
                 metrics=["mae"])
```


In [96]:

```
history_3 = modelLearning(TrainGen,ValGen,model_3,20)
```

Epoch 1/20
300/300 [=====] - 4s 14ms/step - loss: 0.0246
- mae: 0.1259 - val_loss: 0.0173 - val_mae: 0.1051

Epoch 2/20
300/300 [=====] - 5s 17ms/step - loss: 0.0181
- mae: 0.1086 - val_loss: 0.0143 - val_mae: 0.0964

Epoch 3/20
300/300 [=====] - 4s 14ms/step - loss: 0.0146
- mae: 0.0966 - val_loss: 0.0144 - val_mae: 0.0945

Epoch 4/20
300/300 [=====] - 4s 14ms/step - loss: 0.0120
- mae: 0.0881 - val_loss: 0.0105 - val_mae: 0.0823

Epoch 5/20
300/300 [=====] - 4s 14ms/step - loss: 0.0110
- mae: 0.0835 - val_loss: 0.0093 - val_mae: 0.0763

Epoch 6/20
300/300 [=====] - 4s 14ms/step - loss: 0.0104
- mae: 0.0810 - val_loss: 0.0083 - val_mae: 0.0717

Epoch 7/20
300/300 [=====] - 4s 14ms/step - loss: 0.0102
- mae: 0.0803 - val_loss: 0.0108 - val_mae: 0.0809

Epoch 8/20
300/300 [=====] - 4s 14ms/step - loss: 0.0099
- mae: 0.0792 - val_loss: 0.0093 - val_mae: 0.0762

Epoch 9/20
300/300 [=====] - 4s 14ms/step - loss: 0.0095
- mae: 0.0766 - val_loss: 0.0086 - val_mae: 0.0733

Epoch 10/20
300/300 [=====] - 4s 14ms/step - loss: 0.0092
- mae: 0.0757 - val_loss: 0.0087 - val_mae: 0.0724

Epoch 11/20
300/300 [=====] - 4s 14ms/step - loss: 0.0093
- mae: 0.0759 - val_loss: 0.0080 - val_mae: 0.0699

Epoch 12/20
300/300 [=====] - 4s 14ms/step - loss: 0.0085
- mae: 0.0724 - val_loss: 0.0084 - val_mae: 0.0731

Epoch 13/20
300/300 [=====] - 4s 14ms/step - loss: 0.0087
- mae: 0.0739 - val_loss: 0.0069 - val_mae: 0.0666

Epoch 14/20
300/300 [=====] - 5s 15ms/step - loss: 0.0088
- mae: 0.0733 - val_loss: 0.0076 - val_mae: 0.0686

Epoch 15/20
300/300 [=====] - 4s 14ms/step - loss: 0.0090
- mae: 0.0742 - val_loss: 0.0089 - val_mae: 0.0740

Epoch 16/20
300/300 [=====] - 4s 14ms/step - loss: 0.0088
- mae: 0.0739 - val_loss: 0.0082 - val_mae: 0.0715

Epoch 17/20
300/300 [=====] - 4s 14ms/step - loss: 0.0091
- mae: 0.0751 - val_loss: 0.0087 - val_mae: 0.0741

Epoch 18/20
300/300 [=====] - 5s 16ms/step - loss: 0.0076
- mae: 0.0686 - val_loss: 0.0080 - val_mae: 0.0711

Epoch 19/20
300/300 [=====] - 4s 14ms/step - loss: 0.0083
- mae: 0.0714 - val_loss: 0.0093 - val_mae: 0.0768

Epoch 20/20

300/300 [=====] - 4s 15ms/step - loss: 0.0092
- mae: 0.0744 - val_loss: 0.0079 - val_mae: 0.0692

In [133]:

```
model_3.evaluate(TestGen, steps = 500)
```

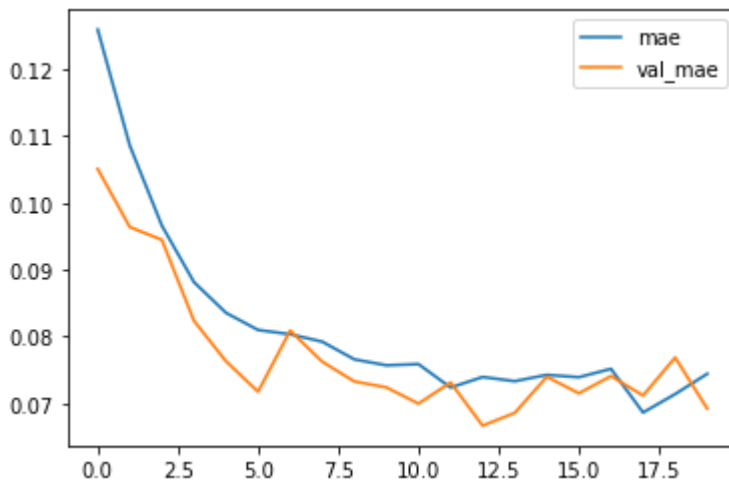
500/500 [=====] - 4s 8ms/step - loss: 0.0079 -
mae: 0.0698

Out[133]:

```
[0.007945071905851364, 0.06978649646043777]
```

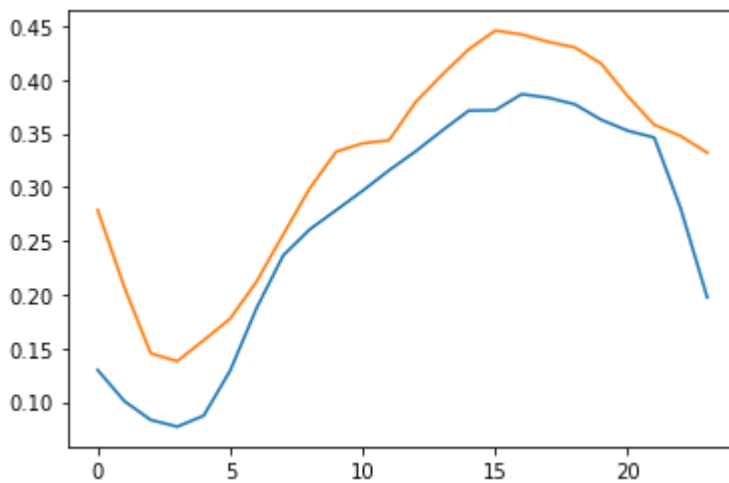
In [98]:

```
plotHistory(history_3)
```



In [136]:

```
plotGraph(model_3)
```



In [108]:

```
def createRNNmodelplus():
    model = Sequential()
    model.add(GRU(32,
                  dropout = 0.1,
                  recurrent_dropout = 0.4,
                  input_shape = (None, 1),
                  return_sequences=True))
    model.add(GRU(64, dropout = 0.1, input_shape = (None, 1)))
    model.add(Dense(1,activation = "sigmoid"))
    model.summary()
    return model
```

In [113]:

```
model_4 = createRNNmodelplus()
```

WARNING:tensorflow:Layer gru_8 will not use cuDNN kernel since it does n't meet the cuDNN kernel criteria. It will use generic GPU kernel as fallback when running on GPU

WARNING:tensorflow:Layer gru_9 will not use cuDNN kernel since it does n't meet the cuDNN kernel criteria. It will use generic GPU kernel as fallback when running on GPU

Model: "sequential_24"

Layer (type)	Output Shape	Param #
gru_8 (GRU)	(None, None, 32)	3360
gru_9 (GRU)	(None, 64)	18816
dense_44 (Dense)	(None, 1)	65

Total params: 22,241

Trainable params: 22,241

Non-trainable params: 0

In [114]:

```
model_4.compile(loss='mse',
                optimizer = 'rmsprop',
                metrics=["mae"])
```

In [115]:

```
history_4 = modelLearning(TrainGen,ValGen,model_4,20)
```

Epoch 1/20
300/300 [=====] - 32s 106ms/step - loss: 0.021
6 - mae: 0.1173 - val_loss: 0.0174 - val_mae: 0.1055

Epoch 2/20
300/300 [=====] - 32s 108ms/step - loss: 0.016
9 - mae: 0.1039 - val_loss: 0.0104 - val_mae: 0.0830

Epoch 3/20
300/300 [=====] - 32s 108ms/step - loss: 0.015
2 - mae: 0.0964 - val_loss: 0.0099 - val_mae: 0.0784

Epoch 4/20
300/300 [=====] - 33s 110ms/step - loss: 0.012
9 - mae: 0.0887 - val_loss: 0.0080 - val_mae: 0.0711

Epoch 5/20
300/300 [=====] - 33s 110ms/step - loss: 0.011
9 - mae: 0.0847 - val_loss: 0.0091 - val_mae: 0.0754

Epoch 6/20
300/300 [=====] - 33s 110ms/step - loss: 0.011
1 - mae: 0.0822 - val_loss: 0.0105 - val_mae: 0.0814

Epoch 7/20
300/300 [=====] - 33s 110ms/step - loss: 0.011
9 - mae: 0.0851 - val_loss: 0.0079 - val_mae: 0.0691

Epoch 8/20
300/300 [=====] - 32s 108ms/step - loss: 0.010
8 - mae: 0.0806 - val_loss: 0.0083 - val_mae: 0.0716

Epoch 9/20
300/300 [=====] - 33s 108ms/step - loss: 0.010
3 - mae: 0.0796 - val_loss: 0.0085 - val_mae: 0.0720

Epoch 10/20
300/300 [=====] - 33s 110ms/step - loss: 0.009
2 - mae: 0.0741 - val_loss: 0.0112 - val_mae: 0.0832

Epoch 11/20
300/300 [=====] - 33s 111ms/step - loss: 0.010
1 - mae: 0.0790 - val_loss: 0.0081 - val_mae: 0.0707

Epoch 12/20
300/300 [=====] - 33s 111ms/step - loss: 0.009
5 - mae: 0.0764 - val_loss: 0.0083 - val_mae: 0.0728

Epoch 13/20
300/300 [=====] - 33s 109ms/step - loss: 0.008
8 - mae: 0.0736 - val_loss: 0.0073 - val_mae: 0.0678

Epoch 14/20
300/300 [=====] - 33s 109ms/step - loss: 0.009
2 - mae: 0.0747 - val_loss: 0.0072 - val_mae: 0.0663

Epoch 15/20
300/300 [=====] - 33s 109ms/step - loss: 0.008
9 - mae: 0.0738 - val_loss: 0.0077 - val_mae: 0.0657

Epoch 16/20
300/300 [=====] - 33s 109ms/step - loss: 0.009
4 - mae: 0.0752 - val_loss: 0.0091 - val_mae: 0.0763

Epoch 17/20
300/300 [=====] - 34s 113ms/step - loss: 0.009
4 - mae: 0.0744 - val_loss: 0.0070 - val_mae: 0.0653

Epoch 18/20
300/300 [=====] - 33s 109ms/step - loss: 0.008
6 - mae: 0.0719 - val_loss: 0.0064 - val_mae: 0.0614

Epoch 19/20
300/300 [=====] - 33s 109ms/step - loss: 0.008
6 - mae: 0.0719 - val_loss: 0.0099 - val_mae: 0.0768

Epoch 20/20

300/300 [=====] - 33s 111ms/step - loss: 0.008

8 - mae: 0.0729 - val_loss: 0.0071 - val_mae: 0.0663

In [116]:

```
model_4.evaluate(TestGen, steps = 500)
```

500/500 [=====] - 6s 11ms/step - loss: 0.0072

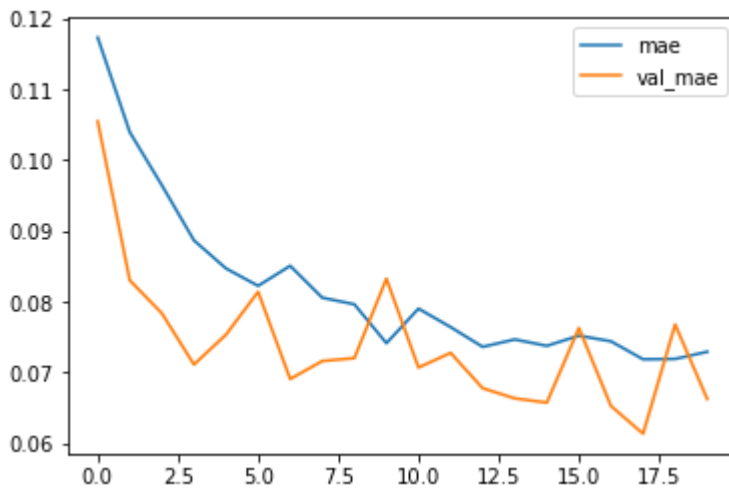
- mae: 0.0670

Out[116]:

```
[0.007208918686956167, 0.06699986010789871]
```

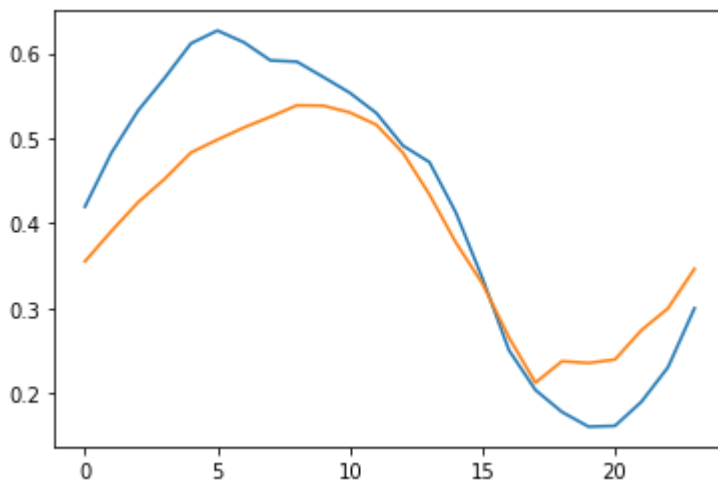
In [120]:

```
plotHistory(history_4)
```



In [144]:

```
plotGraph(model_4)
```



Вывод

Усложненная модель рекуррентной сети дает незначительно лучшее качество, чем однослойная рекуррентная сеть, однако и это значение не превышает до обычного многослойного перцептрона

В ходе работы были разработаны и исследованы модели для прогнозирования временного ряда, все построенные модели дают достаточно хорошее качество и прогнозируемое значение практически совпадает с реальным

Стоит также отметить, что самое лучшее качество прогнозирования показала модель многослойного перцептрона в виду особенности задачи прогнозирования случайного временного ряда. Причина, по которой сверточные и рекуррентные нейронные сети оказались чуть хуже, заключается в отсутствии каких-либо существенных закономерностей в данных, критичных для данных видов сетей.

In []: